AN IMPROVED FUNCTIONAL LINK NEURAL NETWORK FOR DATA CLASSIFICATION

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I would like to dedicate my Doctoral thesis to my beloved parents whose sincere prayers make it possible for me to fulfill their utmost desire. May Allah always bless them with more happiness and good health

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ABSTRACT

The goal of classification is to assign the pre-specified group or class to an instance based on the observed features related to that instance. The implementation of several classification models is challenging as some only work well when the underlying assumptions are satisfied. In order to generate the complex mapping between input and output space to build the arbitrary complex non-linear decision boundaries, neural networks has become prominent tool with wide range of applications. The recent techniques such as Multilayer Perceptron (MLP), standard Functional Link Neural Network (FLNN) and Chebyshev Functional Link Neural Network (CFLNN) outperformed their existing regression, multiple regression, quadratic regression, stepwise polynomials, K-nearest neighbor (K-NN), Naïve Bayesian classifier and logistic regression. This research work explores the insufficiencies of well- known CFLNN model where CFLNN utilizes functional expansion with large number of degree and coefficient value for inputs enhancement which increase computational complexity of the network. Accordingly, two alternative models namely; Genocchi Functional Link Neural Network (GFLNN) and Chebyshev Wavelets Functional Link Neural Network (CWFLNN) are proposed. The novelty of these approaches is that, GFLNN presents the functional expansions with less degree and small coefficient values to make less computational inputs for training to overcome the drawbacks of CFLNN. Whereas, CWFLNN is capable to generate more number of small coefficient value based basis functions with same degree of polynomials as compared to other polynomials and it has orthonormality condition therefore it has more accurate constant of functional expansion and can approximate the functions within the interval. These properties of CWFLNN are used to overcome the deficiencies of GFLNN. The significance of proposed models is verified by using statistical tests such as Freidman test based on accuracy ranking and pairwise comparison test. Moreover, MLP, standard FLNN and CFLNN are used for comparison. For experiments, benched marked data sets from UCI repository,

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SVMLIB data set and KEEL data sets are utilized. The CWFLNN reveals significant improvement (due to its generating more numbers of basis function property) in terms of classification accuracy and reduces the computational work.

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ABSTRAK

Matlamat klasifikasi adalah untuk menentukan pra-penetapan kumpulan atau kelas kepada kriteria berdasarkan ciri-ciri yang berkaitan dengan kriteria tersebut. Terdapat cabaran dalam melaksanakan beberapa model klasifikasi kerana ianya hanya berjalan lancar sekiranya memenuhi andaian asas. Bagi menjana pemetaan yang kompleks di antara ruang input dan output untuk membangunkan sempadan keputusan tidak linear yang kompleks sebarangan, rangkaian neural telah menjadi alat yang penting dengan aplikasi yang meluas. Model-model terkini seperti *Multilayer Percetpron* (MLP), asas *Functional Link Neural Network* (FLNN) dan *Chebyshev Functional Link Neural Network* (CFLNN) mengatasi regresi sedia ada, regresi berbilang, regresi kuadratik, polinomial berperingkat *K-nearest neighbor* (K-NN), pengelas Naïve Bayesian dan regresi logistik. Kajian ini meneliti kekurangan CFLNN yang terkenal penggunaannya, di mana CFLNN menggunakan pengembangan fungsian dengan jumlah yang besar dan nilai pekali untuk penambahan input, ini menyebabkan peningkatan ketidakstabilan rangkaian CFLNN. Oleh itu, dua teknik alternatif iaitu *Genocchi Functional Link Neural Network* (GFLNN) dan *Chebyshev Wavelets Functional Link Neural Network* (CWFLNN) telah dicadangkan. Novelti pendekatan ini adalah GFLNN memberikan pengembangan fungsian dengan jumlah yang sedikit dan nilai pekali yang kecil untuk mengurangkan pengiraan input dalam proses latihan rangkaian bagi menambahbaik kekurangan CFLNN. Oleh itu, CWFLNN mampu menjana lebih banyak fungsi pekali kecil berdasarkan nilai polinomial yang sama dengan polinomial lain dan mempunyai keadaan ortonormaliti sehingga ia mempunyai pengembangan fungsi yang lebih tepat dan boleh menghitung fungsi dalam sela waktu. Ciri-ciri CWFLNN ini digunakan untuk mengatasi kekurangan GFLNN. Keberkesanan model yang dicadangkan disahkan dengan pengujian statistik seperti pengujian Freidman, di mana ia berasaskan penilaian ketepatan dan pengujian perbandingan berpasangan. Selain itu, model MLP, asas FLNN dan CFLNN digunakan sebagai perbandingan model. Data set

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daripada UCI, SVMLIB dan KEEL digunakan dalam proses eksprimen. CWFLNN menunjukkan peningkatan (kerana ia menjana lebih banyak bilangan fungsi-fungsi asas) yang signifikan dari segi ketepatan klasifikasi dan pengurangan kerja pengiraan.

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LIST OF SYMBOLS AND ABBREVIATION

ANNs	–	Artificial Neural Networks
HONNS	–	Higher Order Neural Networks
MLP	–	Multilayer Perceptron
CMLP	–	Chebyshev Multilayer Perceptron
FLNN	–	Functional Link Neural Network
F.E	–	Functional Expansion
CFLNN	–	Chebyshev Functional Link Neural Network
LeFLNN	–	Legendre Functional Link Neural Network
GFLNN	–	Genocchi Functional Link Neural Network
CWFLNN	–	Chebyshev Wavelet Functional Link Neural Network
B.P	–	Back Propagation
LM	–	Levenberg- Marquardt

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LIST OF PUBLICATIONS

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CHAPTER 1

INTRODUCTION

1.1 Background of Research

Classification has become more active and commonly encountered decision making activity in the field of Artificial Neural Networks (ANN) (Al-jarrah, 2015; Chen *et al*., 2011; Mason, 2015; Misra and Dehuri, 2007; Zhang, 2000). This problem occurs when an object needs to be assigned to a specific class or group on the basis of its attributes related to that objects. There are two basic steps of classification; first step is to construct the model, where set of example records known as training set is needed, which is presented to ANN so that network can "learn" the pattern. During the training of network, each record set in the training set consists of numerous features. In features contained training set, one attribute known as classifying attribute is mainly used for the indication of the class to which each record is related. After that, based on the functional relationship between classifying attribute and other attributes of training set record, ANN creates the classifier (classification model). In second step, this new build classifier is used to classify the unseen record (out of sample record). Numbers of real world application examples on neural classification tasks include credit scoring, quality control, speech recognition, fault decision, bankruptcy prediction and medical diagnosis.

In Machine Learning (ML), ANNs is the group of statistical learning algorithms which is inspired from the working of information processing in human brain (Michalski *et al.*, 2013). That is capable of changing its structure based on provided internal and external information due to the data driven self-adaptive

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property. After that, this information flows from network to model complex relationship of inputs and outputs. The great interest in neural classification based research activities have shown that the ANNs are the promising tools and have been extensively utilized to several numbers of real world classification tasks such as in science, medical, business and industry (Abbadi and Kadhim, 2017; Al-jarrah, 2015; Al-shayea, 2011; Ghazali *et al.*, 2011; Li *et al.*, 2014; Liao and Wen, 2007; Manik *et al.*, 2016; Mazurowski *et al.*, 2008; Zhang, 2000). One of the most common and best-known ANNs type is the Multilayer Perceptron (MLP). MLP is extensively used and famous model for classification tasks. The training capability and nonlinear nature of MLP has shown that the network has better performance as compared to statistical method for classification task (Murtagh, 1991; Paliwal and Kumar, 2009; Walde *et al.*, 2003; Zare *et al.*, 2014) and sometime it requires long training time due to multilayer structure.

Beside the development of numerous kinds of ANNs, this research work focuses on Higher Order Neural Network (HONNs) namely on Functional Link Neural Network (FLNN) to examine the ability of the network for solving the classification problems. FLNN is a single layer neural network (Giles and Maxwell, 1987) and is a class of HONNs, which can perform nonlinear mapping, using single layer of units (Giles and Maxwell, 1987). To achieve the nonlinear separability to reduce the complexity, HONNs utilize the high order terms to expand inputs into high dimensional space. This single layer property in FLNN also makes it more preferable because it also reduces the complexity of learning algorithm of the network as compared to other feedforward standard neural networks (Misra and Dehuri, 2007; Bebarta & Dash, 2012; Kumar *et al.*, 2015; Babaei *et al.*, 2017).

In neural classification, training of the network is important in case of building a classification model. In this research, functional expansions based FLNN is considered for neural classification task (Patra and Kot, 2002; Patra and Pal, 1995; Weng *et al.*, 2007; Hema *et al.*, 2008; Cho, 2009; Majhi *et al.*, 2010; Bebarta *et al.*, 2012; Kumar et al., 2015). This network is useful for handling the non-linear non-separable problems with suitable input representation. The suitable enhanced inputs are dependent on the basis functions, trigonometric functions and power series.

Researchers have used different types of basis functions and trigonometric functions as functional expansion (F.E) in FLNN. Chebyshev Polynomials, Legendre Polynomials, Laguerre Polynomials and $Tanh$ function are some commonly applied

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functional expansions (Babaei *et al.,* 2017; Dehuri and Cho, 2010b; Li *et al.,* 2012; Mall and Chakraverty, 2016; Mishra *et al.,* 2009; Patra and Kot, 2002; Patra and Pal, 1995; Weng *et al.,* 2007). After the selection of suitable basis function, this function is used to increase the dimension of space. These expanded inputs are then used for the training of the network instead of actual inputs data. In this scenario, higher order input terms are selected so that they are linearly independent of the original pattern components.

In HONNs, especially for F.E based FLNN, it can be noted that the enhancement of the input patterns is much effective for the solution of neural classification problems. Hence this research proposes the use of an improved basis function as F.E with FLNN; namely Genocchi Polynomials (Loh *et al.,* 2017) and Chebyshev wavelets (Isah & Chang, 2017), in order to reduce the complexity of enhanced inputs which increase the accuracy of the neural network for classification tasks. These expansions are able to recover the drawbacks of Chebyshev Polynomials, Legendre Polynomials, and Laguerre Polynomials.

1.2 Problem Statement

The implementation of ANN pertains to different type of classification problems and appearing as promising modeling tool have made them very successful as compared to classical statistical approaches (Benediktsson *et al.,* 1990; Gorr *et al.,* 1994; Paliwal and Kumar, 2009). It is due to the data driven self- adaptive and universal approximator properties (Cybenko, 1989; Hornik *et al.,* 1989; Zhang, 2000; Richard and Lippmann, 1991; Zhang, 2000; González & Zamarreño, 2005; Khashei & Bijari, 2010; Ben Ali *et al.,* 2015; Zhang, 2018). MLP which is best known type of ANNs is a feed forward multilayer structural model. This model has been extensively applied on various class of classification (Silva, 2008; Zabidi *et al.,* 2010; Thomas & Suhner, 2015; Zhang *et al.,* 2016).

Besides the advantages, MLP has burden of computationally intensive training and local minima in the error surface (Parappa and Singh, 2013; Yu, 2005). MLP also needs large number of available measures and it is not capable of making high order correlation among inputs to construct high order network to perform non-linear mapping.

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To overcome the MLP draw backs, functional expansion based layer is added in the network structure of MLP. The model is a combination of the characteristics of Chebyshev orthogonal polynomial and multilayer perceptron, which is named as CMLP. Moreover, where CMLP has improved the accuracy of classification task, at the same time it also has problem of multilayer structure which cause of increasing the computational complexity of the network.

To overcome the insufficiencies in CMLP, single layer units based Functional Link Neural Network (FLNN) is considered with the ability of performing nonlinear mapping (Pao and Takefuji, 1992). Pao has proposed two types of FLNN models; F.E model and tensor (outer product) model also known as standard FLNN model. In standard FLNN, Pao suggested that higher order terms beyond the second order are not required. In addition, two or more equal indices should be omitted in enhanced pattern. This is the limitation of this model. Moreover, it produces inconsistent results due to less number of parameters and local minima trapping due to inherit problem exist in gradient based learning (Hassim, 2016). On the other hand, the functional link acts on each node singly, in which it simply applies one or more univariate functions to each input. This model is used to expand the dimensions of inputs without introducing joint activation and without any interaction between inputs. F.E model is based on the basis function that can be selected according to the nonlinear problems for more accurate classification. There is no concept of order of higher order terms; therefore by selecting good basis function, this model performs better than the tensor. The limitations of this model is that it is hard to select appropriate basis function and as the degree of polynomials increase the complexity of enhanced inputs also increase (Li *et al.*, 2012a; Hassim, 2016). Therefore, restriction of higher order terms and absence of basis function in standard FLNN model make it limited for better classification as compared to F.E model where selection of good approximate basis functions and tacking of high dimensions problems made it adoptive.

Meanwhile, in the research of F.E based FLNN, the enhancement of inputs is important factor which also affects the training of the network. Mostly successfully known functional expansions are Chebyshev Polynomials, Legendre Polynomials, Laguerre Polynomials and trigonometric functions (Bebarta *et al.*, 2012). Chebyshev Polynomials, Legendre Polynomials and Laguerre Polynomials are mostly used as F.E due to their orthogonal property and function approximation property. On the

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other hand, these polynomials have some drawbacks such as enhanced inputs values which are generated by these known polynomials have large value which affect the computational complexity of the network and increase the complexity of the network which needed to be focus to improve the classification accuracy. To overcome the gaps in CFLNN, LFLNN and LeFLNN, non-orthogonal Genocchi polynomials based FLNN (GFLNN) was proposed. These non-orthogonal polynomials are better approximators as compared to orthogonal polynomials due to certain characteristics. Firstly, Genocchi polynomials have less number of terms than the Chebyshev, Legendre and Laguerre polynomials which means that with increasing degree of polynomials, the number of terms also increases. Secondly, the coefficients of individual terms in Genocchi polynomials are smaller than the coefficients of individual terms in the classical orthogonal polynomials. Since the computational errors are related to the coefficient of individual terms, the computational errors are less by using Genocchi polynomials.

On the other side, in Genocchi polynomials based FLNN constant of expansion is not more accurate due to orthogonality and it do not has compact support where they can approximate the function within the interval. Additionally, it is also not capable to generate more number of basis functions with small value and same degree (means using 3rd degree of polynomials). Based on all these properties which do not exist in Genocchi polynomials, Chebyshev wavelets based FLNN (CWFLNN) is intend to propose because Chebyshev wavelets have orthonormality condition which has more accurate constant of F.E. Moreover, these wavelets can generate more number of basis functions on the same degree as compared to Genocchi polynomials. This proposed model is also used for the input enhancement with more small inputs value terms and less computational task which helps the training in more effective way.

1.3 Research Questions

The goal of this research can be addressed by the following research questions:

1. How to find out the most suitable functional expansions for FLNN in order to generate less complicated enhanced inputs?

2. How to overcome the drawbacks of CFLNN by implementing the Genocchi polynomials as functional expansion?
3. How to derive Chebyshev wavelets in enhancing data classification performance?
4. What are the limitations posed by Genocchi polynomials and Chebyshev wavelets when used with FLNN?

1.4 Research Aim and Objectives

The aim of this research is to introduce the improved F.E layer in FLNN to generate the less complex enhanced inputs. Different types of basis functions such as Genocchi polynomials with less number of terms and small coefficient values of individual terms and Chebyshev wavelets with more numbers of small value basis functions using same degree are implemented with FLNN to improve the classification task. As a result of these expansions, the classification accuracy will be improved. To achieve the research aim, following are the objectives:

1. To implement the Genocchi polynomials as F.E layer in FLNN (GFLNN) in order to overcome the insufficiencies of Chebyshev FLNN.
2. To develop the Chebyshev Wavelets based FLNN (CWFLNN) in order to tackle the drawbacks that occur in GFLNN.
3. To evaluate and compare the performance of CWFLNN with existing models based on some evaluation measures.

1.5 Scope of Research

This research highlights the construction, implementation and testing of FLNN with implementation of Chebyshev Wavelet for classification task. The input enhancement structure of FLNN is based on functional expansion model structure. Later, results are compared with MLP, CFLNN and standard FLNN. All neural network models are tested and evaluated on various benchmark classification problems to check the performance of classification tasks.

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